exploreafnrgvsec-exercise (Victor Ashioya)

December 7, 2022

[1]:
```python
import pandas as pd
import numpy as np
import seaborn as sns
from matplotlib import pyplot as plt
from scipy import stats
```

[2]:
```python
nrgvsecon=pd.read_csv("africanrgvsgdrp.csv",index_col=[0])
nrgvsecon.shape
```

[2]:
```
(52, 12)
```

0.0.1 Electricity Generation Sources in each country

We will start by seeing the different electricity generation sources in different countries

[3]:
```python
nrgvsecon.head(5)
```

[3]:
```
        country   population  real gdp per capita $  installed capacity kW  \
0       nigeria  225082083.0                 4900.0             11691000.0
1         egypt  107770524.0                12000.0             59826000.0
2  south-africa   57516665.0                11500.0             62728000.0
3       algeria   44178884.0                10700.0             21694000.0
4       morocco   36738229.0                 6900.0             14187000.0

   fossil fuels  nuclear  solar  wind  hydroelectricity  tide and wave  \
0          78.1      0.0    0.2   0.0              21.7            0.0
1          88.7      0.0    1.0   2.5               7.7            0.0
2          87.9      5.2    1.6   2.6               2.5            0.0
3          98.9      0.0    0.9   0.0               0.1            0.0
4          81.6      0.0    1.1  13.0               4.4            0.0

   geothermal  biomass and waste
0         0.0                0.1
1         0.0                0.2
2         0.0                0.2
3         0.0                0.0
4         0.0                0.0
```

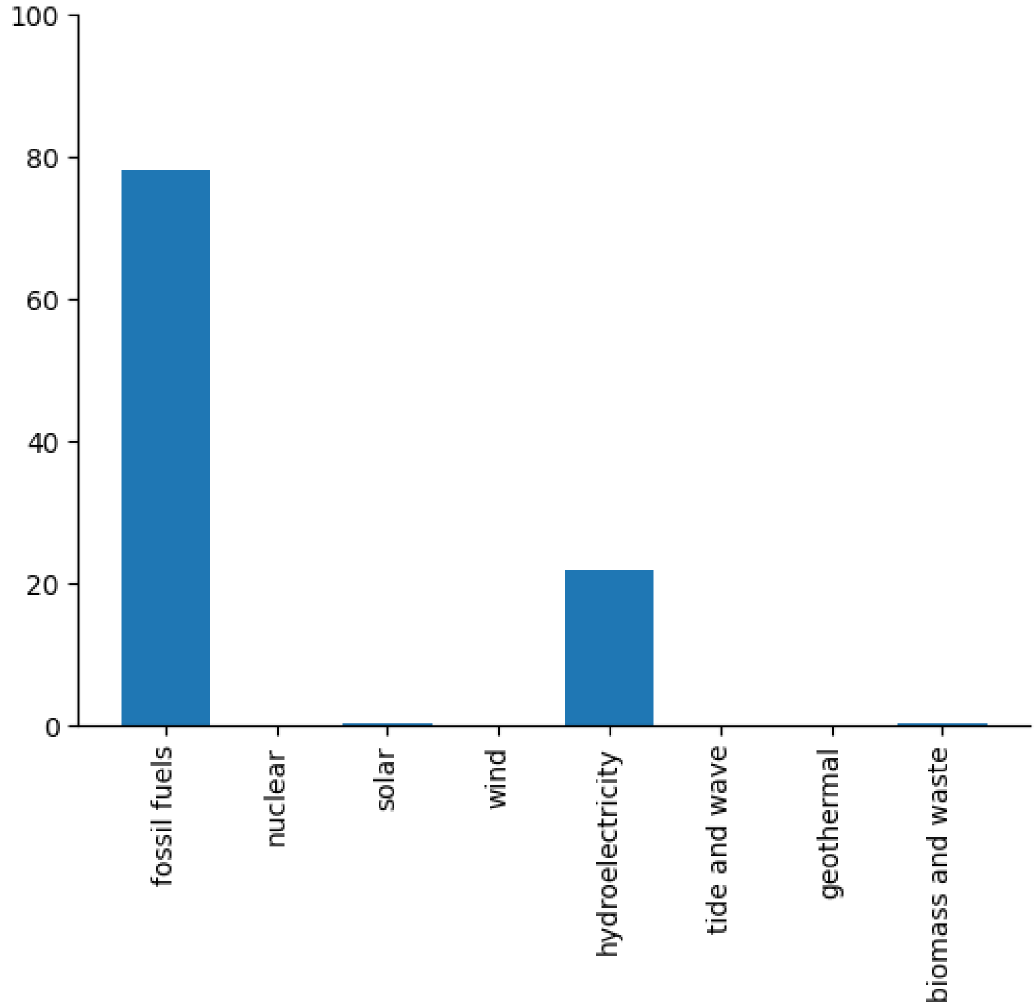
[4]:
```
import matplotlib as mpl

mpl.rcParams['axes.spines.top'] = False
mpl.rcParams['axes.spines.right'] = False
```

[5]:
```
nrgvsecon.iloc[0]
```

[5]:
```
country                        nigeria
population                225082083.0
real gdp per capita $           4900.0
installed capacity kW       11691000.0
fossil fuels                      78.1
nuclear                            0.0
solar                              0.2
wind                               0.0
hydroelectricity                  21.7
tide and wave                      0.0
geothermal                         0.0
biomass and waste                  0.1
Name: 0, dtype: object
```

We will use bar charts to compare different electricity generation sources.ie. `plt.bar()`

[6]:
```
x=nrgvsecon.iloc[0].index[4:]
y=nrgvsecon.iloc[0].values[4:]
orderedy=nrgvsecon.iloc[0].value_counts().index
plt.bar(x,y)
plt.xticks(rotation=90)
plt.ylim(0,100)



plt.show()
```



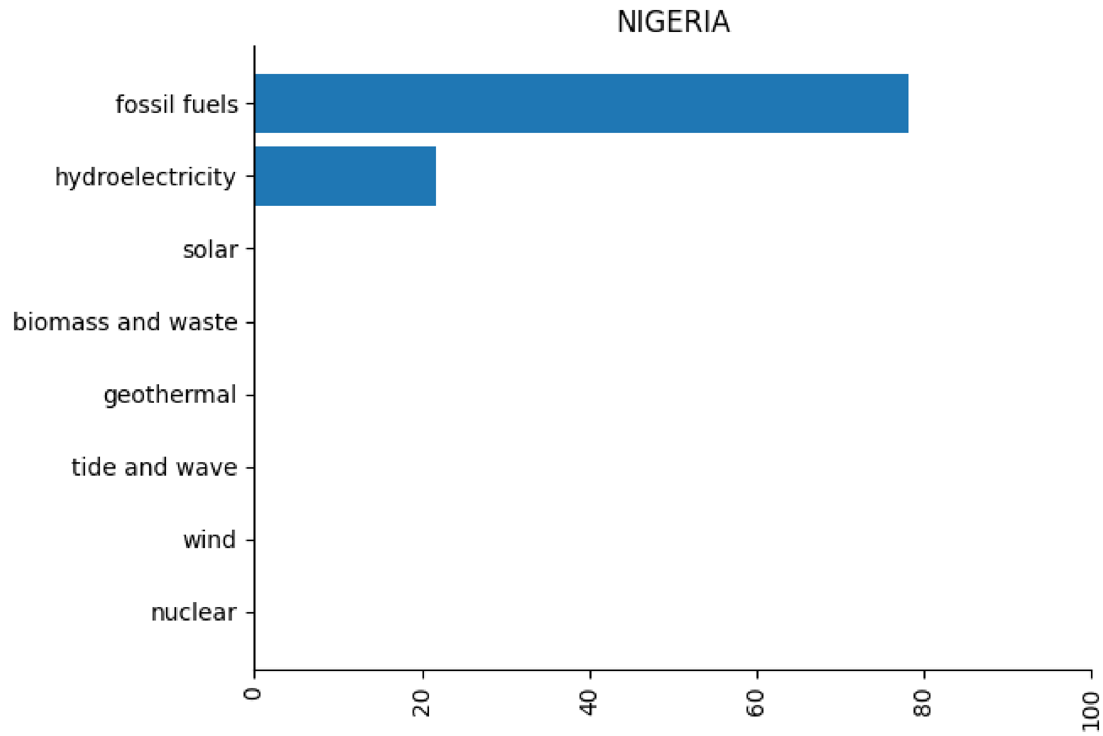
We can see the comparisons of each electricity generation source in a country(in this case, Nigeria).

Now, a better way to visualize this would be the bar charts in some order.e.g. the highest sources to the lowest.

[7]:
```
# argsort returns an array of indices in order ascending order
order=np.argsort(nrgvsecon.iloc[0].values[4:])
```

[8]:
```
# barh will plot a horizontal bar instead of a vertical one
x=nrgvsecon.iloc[0].index[4:][order]
y=nrgvsecon.iloc[0].values[4:][order]
orderedy=nrgvsecon.iloc[0].value_counts().index
fig=plt.barh(x,y)
plt.xticks(rotation=90)
plt.xlim(0,100)
plt.title(nrgvsecon['country'][0].upper())
```

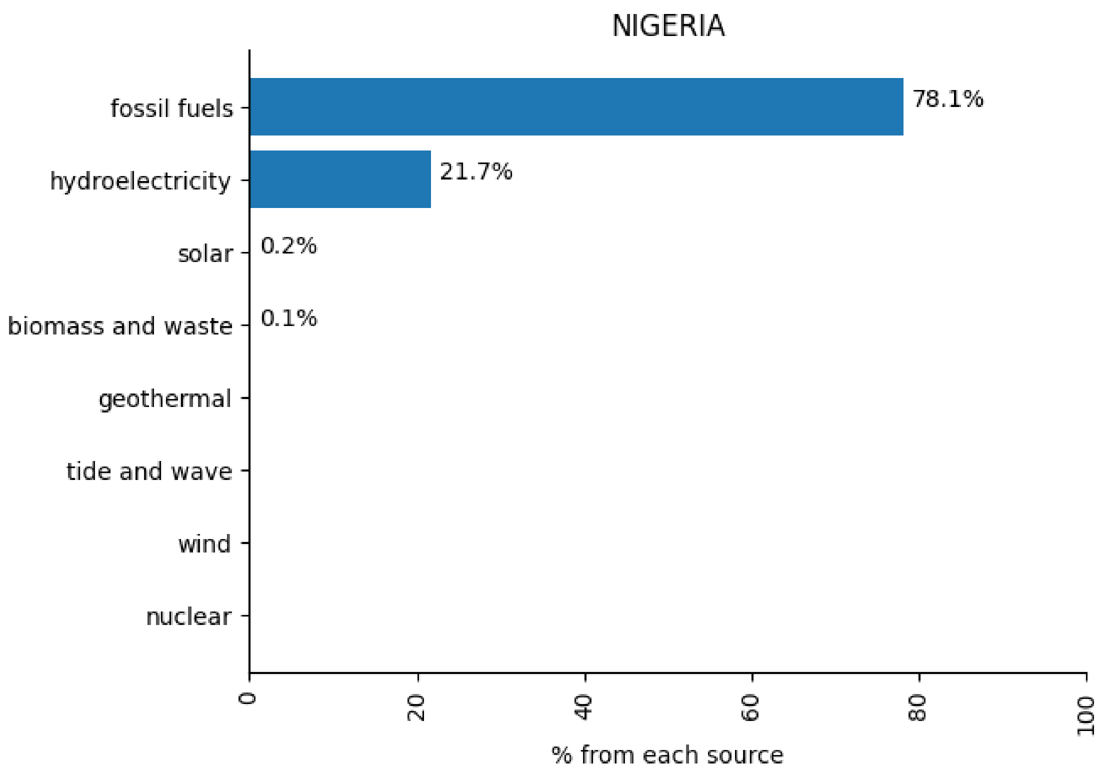
```
plt.show()
```



Another interesting and more clear way to do things would be to have the percent appear at the end of each bar.

We can use `plt.text` to do this

[9]:
```
x=nrgvsecon.iloc[0].index[4:][order]
y=nrgvsecon.iloc[0].values[4:][order]
orderedy=nrgvsecon.iloc[0].value_counts().index
fig=plt.barh(x,y)
plt.xticks(rotation=90)
plt.xlim(0,100)
plt.xlabel("% from each source")
plt.title(nrgvsecon['country'][0].upper())
for i in range(len(y)):
    if y[i]!=0:
        plt.text(y[i]+1, i,f"{y[i]}%")

plt.show()
```



[10]:
```
# test
# nrgvsecon[nrgvsecon['country'].str.contains('kenya')].iloc[0][2:].index
```

The information on this bar chart is really clear.

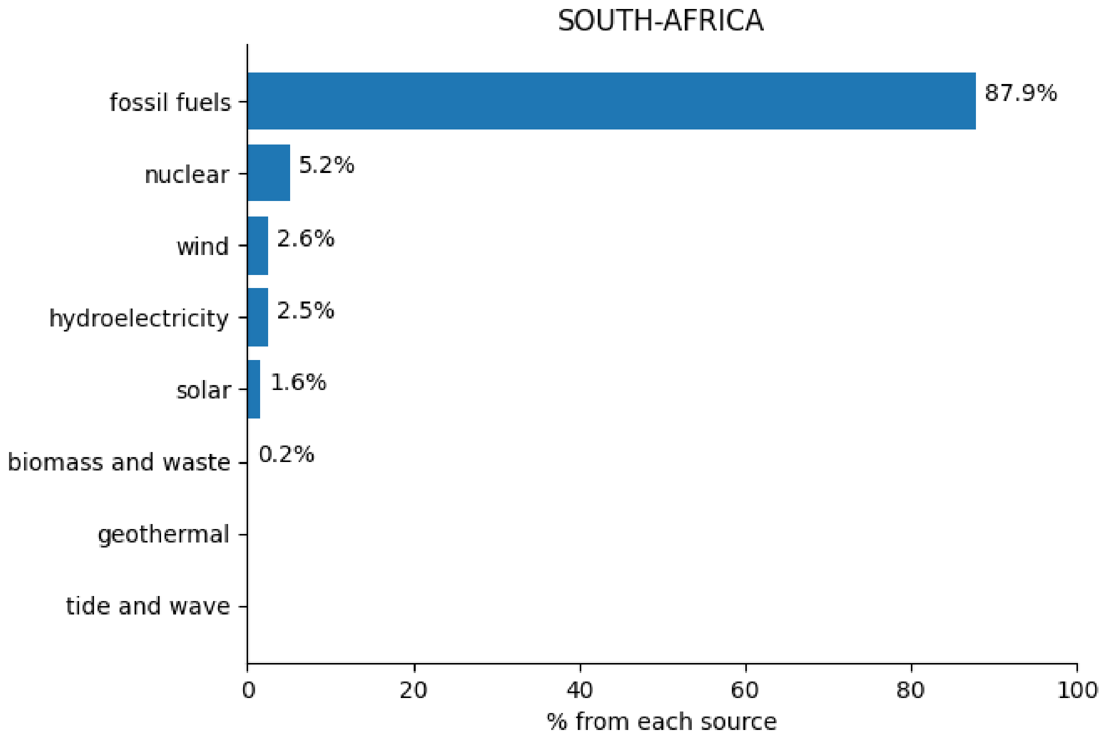
We can see what the percentage contribution from each electricity generation source is!

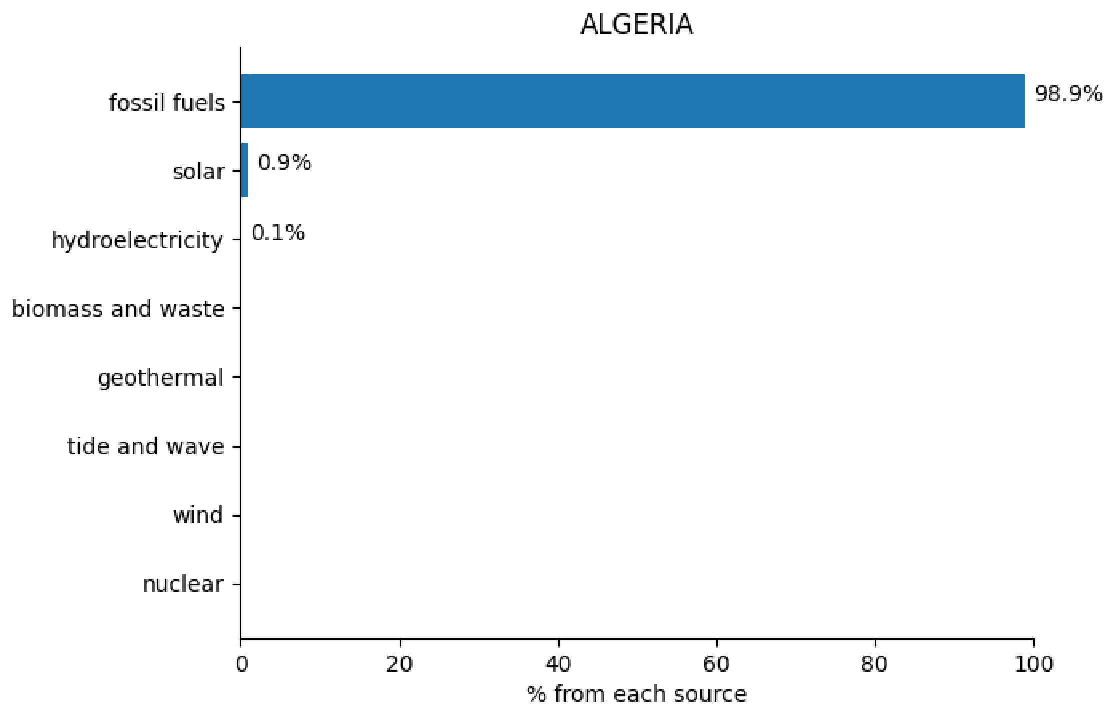
Let's create a function to get this information from any country.

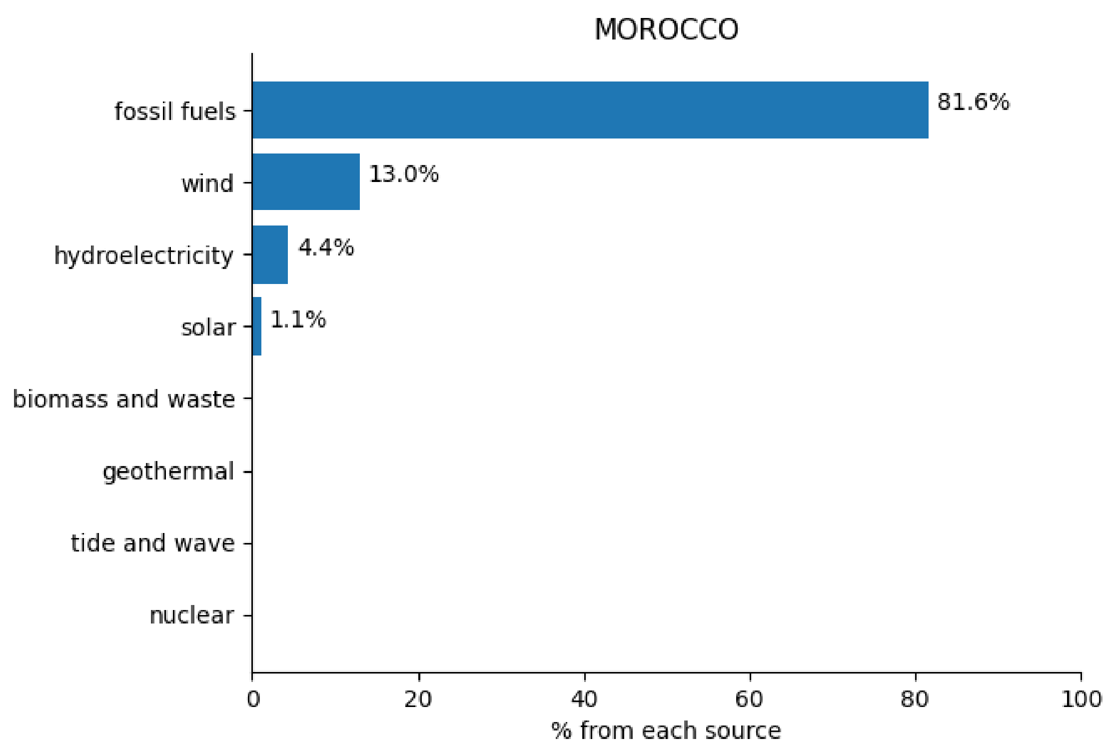
[11]:
```
def plotpercountry(countries):
    for country in countries:
        order=np.argsort(nrgvsecon[nrgvsecon['country'].str.contains(country)].
↪iloc[0].values[4:])
        y=nrgvsecon[nrgvsecon['country'].str.contains(country)].values[0][4:
↪][order]
        x=nrgvsecon[nrgvsecon['country'].str.contains(country)].iloc[0][4:].
↪index[order]
        plt.barh(x,y)
        plt.xlim(0,100)
        plt.xlabel("% from each source")
        plt.title(country.upper())
        for i in range(len(y)):
            if y[i]!=0:
```

```
                plt.text(y[i]+1, i,f"{y[i]}%")
        plt.show()
```

[12]:
```
plotpercountry(nrgvsecon.country.values[2:5])
```




ALGERIA
fossil fuels
solar
hydroelectricity
biomass and waste
geothermal
tide and wave
wind
nuclear
98.9%
0.9%
0.1%
0
20
40
60
80
100
% from each source


MOROCCO
fossil fuels
wind
hydroelectricity
solar
biomass and waste
geothermal
tide and wave
nuclear
81.6%
13.0%
4.4%
1.1%
0
20
40
60
80
100
% from each source

[13]:
```
nrgvsecon.head(10)
```

[13]:
```
        country   population  real gdp per capita $  installed capacity kW  \
0       nigeria  225082083.0                 4900.0             11691000.0
1         egypt  107770524.0                12000.0             59826000.0
2  south-africa   57516665.0                11500.0             62728000.0
3       algeria   44178884.0                10700.0             21694000.0
4       morocco   36738229.0                 6900.0             14187000.0
5        angola   34795287.0                 6200.0              7344000.0
6         kenya   55864655.0                 4200.0              3304000.0
7      ethiopia  113656596.0                 2300.0              4856000.0
8      tanzania   63852892.0                 2600.0              1623000.0
9         ghana   33107275.0                 5300.0              5312000.0

  fossil fuels  nuclear  solar  wind  hydroelectricity  tide and wave  \
0         78.1      0.0    0.2   0.0              21.7            0.0
1         88.7      0.0    1.0   2.5               7.7            0.0
2         87.9      5.2    1.6   2.6               2.5            0.0
3         98.9      0.0    0.9   0.0               0.1            0.0
4         81.6      0.0    1.1  13.0               4.4            0.0
5         28.4      0.0    0.1   0.0              70.1            0.0
6          8.3      0.0    1.0  10.7              32.6            0.0
7          0.0      0.0    0.1   3.8              95.8            0.0
8         65.0      0.0    1.3   0.0              32.8            0.0
9         63.8      0.0    0.3   0.0              35.9            0.0

  geothermal  biomass and waste
0        0.0                0.1
1        0.0                0.2
2        0.0                0.2
3        0.0                0.0
4        0.0                0.0
5        0.0                1.4
6       46.2                1.2
7        0.0                0.3
8        0.0                1.0
9        0.0                0.1
```

0.0.2 Comparing energy sources

Now, we can compare the percentage of energy that Africa produces, and from which each source it comes from.

Let's try do this using a pie chart, and a bar chart.

[14]:
```
# this find the sum of every column
nrgvsecon.sum(numeric_only=True)
```

[14]:
```
population                 1.394572e+09
real gdp per capita $      2.809000e+05
installed capacity kW      2.433790e+08
fossil fuels               3.099700e+03
nuclear                    5.200000e+00
solar                      7.930000e+01
wind                       6.640000e+01
hydroelectricity           1.825700e+03
tide and wave              0.000000e+00
geothermal                 4.620000e+01
biomass and waste          7.870000e+01
dtype: float64
```

[15]:
```
# the sum of the column- installed capacity
totalcapacity=nrgvsecon['installed capacity kW'].sum()
```

[16]:
```
# sum of energy produced by fossil fuels over the total energy produced, to␣
 ↪find the percentage
(np.sum(nrgvsecon['installed capacity kW']*nrgvsecon['fossil fuels']/100))/
 ↪(nrgvsecon['installed capacity kW'].sum())
```

[16]:
```
0.7685277612283722
```

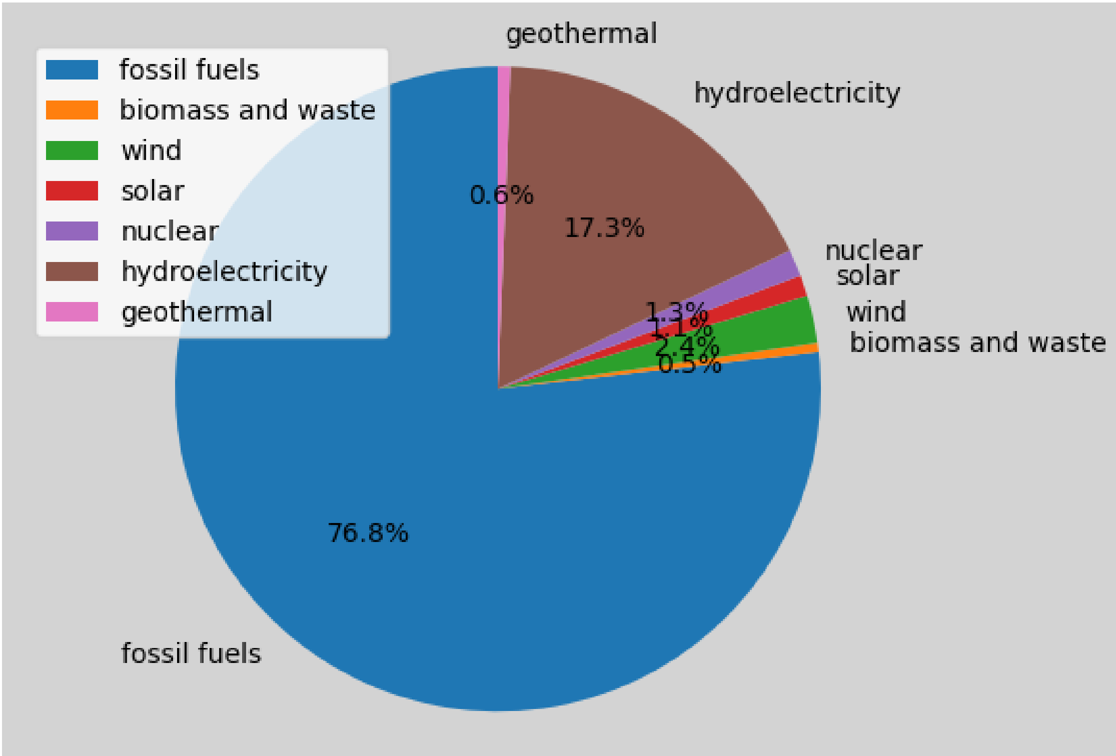
[17]:
```
sources=['fossil fuels','biomass and␣
 ↪waste','wind','solar','nuclear','hydroelectricity','geothermal']
```

[18]:
```
# a function to calculate totals from all sources
def sumcapacity(sources):
  capacities=[]
  for source in sources:
    capacities.append((np.sum(nrgvsecon['installed capacity␣
 ↪kW']*nrgvsecon[source]/100))/totalcapacity)
  return capacities
```

[19]:
```
capas=(sumcapacity(sources))
```

Let's create a simple pie chart.

[20]:
```
fig1, ax1 = plt.subplots()
ax1.pie(capas, labels=sources, autopct='%1.1f%%',
         startangle=90)
ax1.axis('equal')  # Equal aspect ratio ensures that pie is drawn as a circle.
fig1.set_facecolor('lightgrey')
ax1.legend()

plt.show()
```

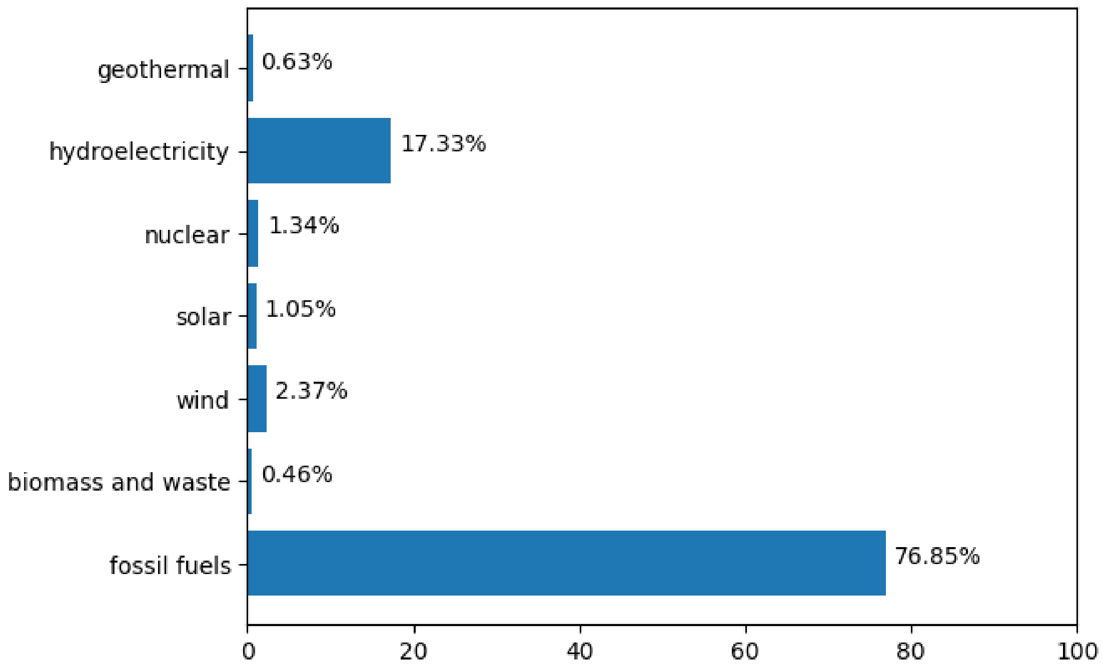


We can clearly see that the highest percentages come from fossil fuels and hydroelectricity.

One question to ask at this point would be whether gdp could still be correlated with electricity generation sources.

For clarity, let's do this again with a bar chart

[21]:
```
mpl.rcParams['axes.spines.top'] = True
mpl.rcParams['axes.spines.right'] = True
plt.barh(sources,(np.array(capas)*100))
plt.xlim(0,100)
for i in range(len(capas)):
    if capas[i]!=0:
        plt.text(capas[i]*100+1, i,f"{(capas[i]*100):.2f}%")
plt.show()
```



0.0.3 gdp

Can we draw some insights on where African gdp's per capita lie? We will use a histogram in this case: `plt.hist` and for seaborn `sns.displot`

[22]:
```
nrgvsecon.head()
```

[22]:
```
        country   population  real gdp per capita $  installed capacity kW  \
0       nigeria  225082083.0                 4900.0             11691000.0
1         egypt  107770524.0                12000.0             59826000.0
2  south-africa   57516665.0                11500.0             62728000.0
3       algeria   44178884.0                10700.0             21694000.0
4       morocco   36738229.0                 6900.0             14187000.0

   fossil fuels  nuclear  solar  wind  hydroelectricity  tide and wave  \
0          78.1      0.0    0.2   0.0              21.7            0.0
1          88.7      0.0    1.0   2.5               7.7            0.0
2          87.9      5.2    1.6   2.6               2.5            0.0
3          98.9      0.0    0.9   0.0               0.1            0.0
4          81.6      0.0    1.1  13.0               4.4            0.0

   geothermal  biomass and waste
0         0.0                0.1
1         0.0                0.2
2         0.0                0.2
```

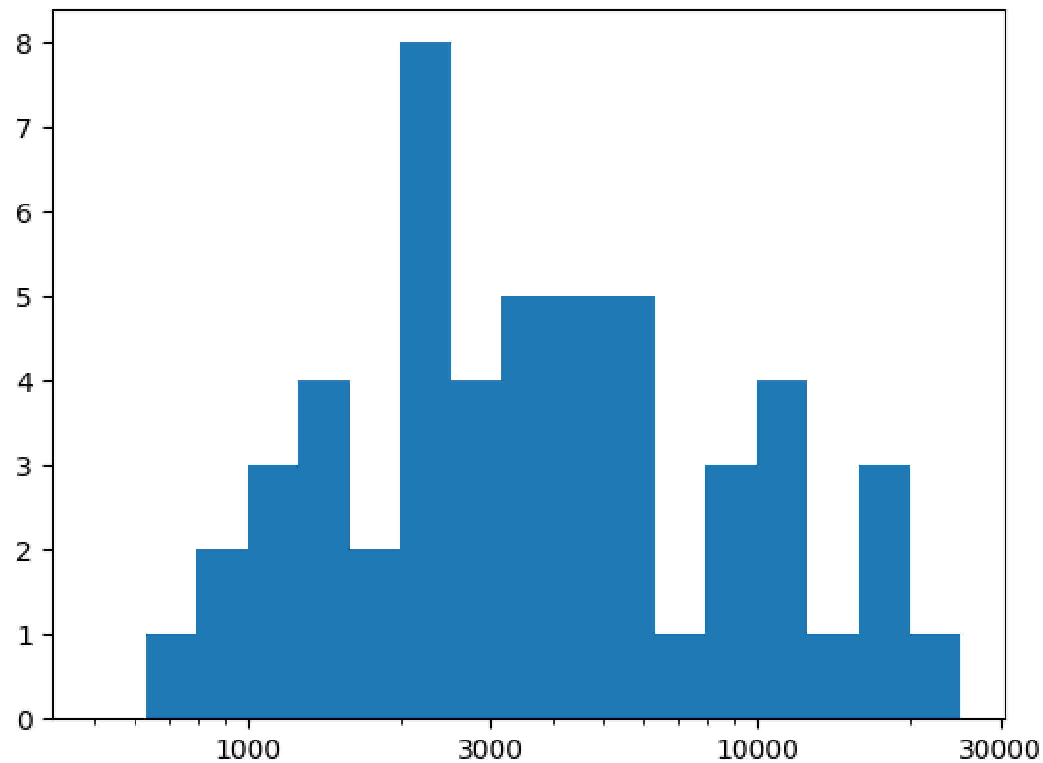
```
3         0.0                 0.0
4         0.0                 0.0
```

[23]:
```
# np.log10(nrgvsecon['real gdp per capita $'].describe())
```

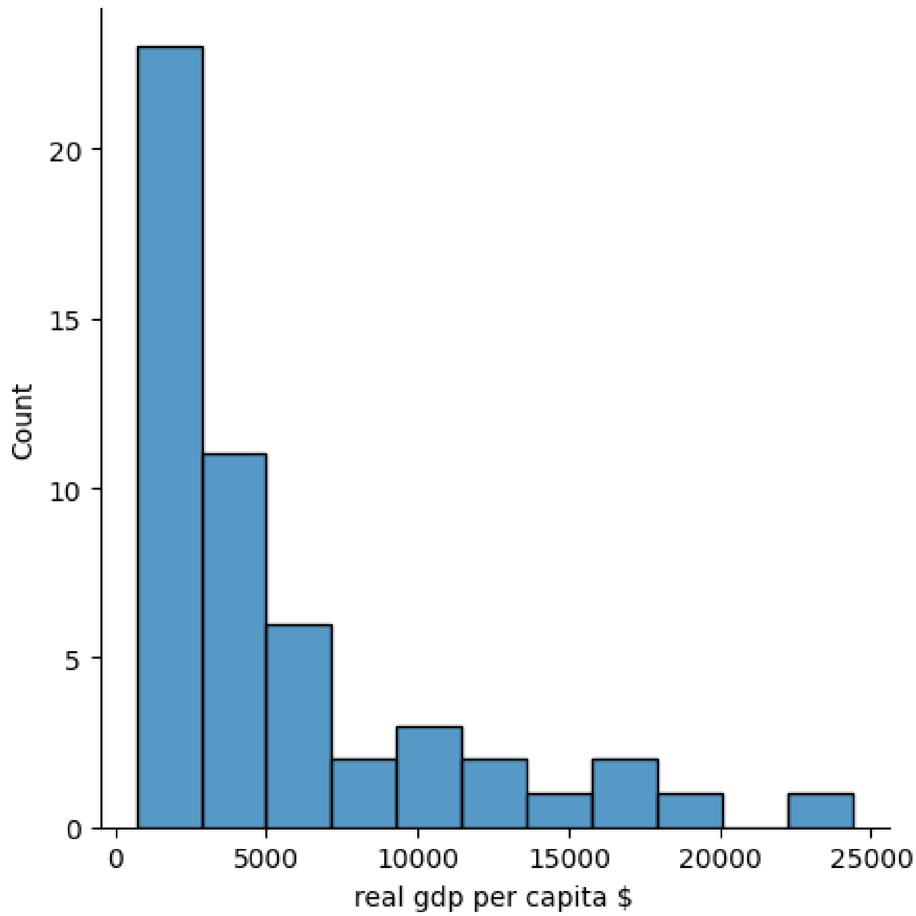
[24]:
```
# 10**np.arange(2.7,4.4+0.1,0.1)
```

[25]:
```
bins=10**np.arange(2.7,4.4+0.1,0.1)
ticks=[1000,3000,10000,30000]
```

[26]:
```
labels=[f'{v}' for v in ticks]
plt.hist(data = nrgvsecon, x='real gdp per capita $',bins=bins)
plt.xscale('log');
plt.xticks(ticks,labels);
```



[27]:
```
sns.displot(nrgvsecon['real gdp per capita $']);
```



It looks like most African countries(more than half) have their real gpd per capita below $ 5000.

What other questions might we have? Do countries with low gdp rely on fossil fuels? Again, is there a correlation between the two?

[28]:
```
nrgvsecon.sort_values('installed capacity kW').head()
```

[28]:
```
                     country  population  real gdp per capita $  \
51      sao-tome-and-principe    217164.0                  4100.0
49              guinea-bissau   2026778.0                  1800.0
50                    comoros    876437.0                  3100.0
45   central-african-republic   5454533.0                   900.0
44                    lesotho   2193970.0                  2300.0

    installed capacity kW  fossil fuels  nuclear  solar  wind  \
51                28000.0          89.5      0.0    0.0   0.0
49                28000.0          97.6      0.0    2.4   0.0
50                35000.0         100.0      0.0    0.0   0.0
45                38000.0           0.7      0.0    0.0   0.0
```

```
44                 74000.0           0.0       0.0    0.2   0.0

    hydroelectricity  tide and wave  geothermal  biomass and waste
51              10.5            0.0         0.0                0.0
49               0.0            0.0         0.0                0.0
50               0.0            0.0         0.0                0.0
45              99.3            0.0         0.0                0.0
44              99.8            0.0         0.0                0.0
```

0.1 Assignment starts here

We can find the correlation between two variables using `scipy.stats`. We imported this module at the beginning of the notebook. It contains functions that compute all the statistics for us!

For example, let's see the spearman rank correlation between installed capacity and gdp per capita.

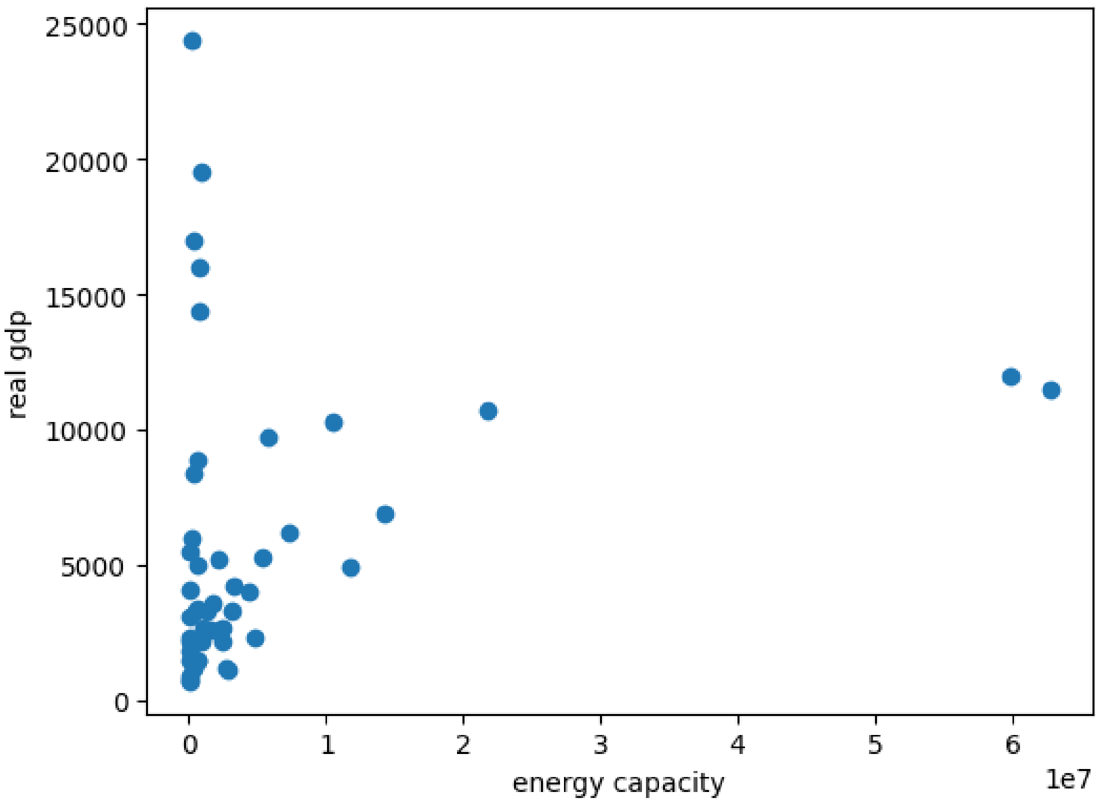
(This may seem like a lot of jargon, but basically, what the function will return is two numbers. The closer the first number(the correlation) is to 1 or -1, the more the variables are alike, otherwise, the closer it is to 0, the less the variables are alike)

[29]:
```
stats.spearmanr(nrgvsecon['installed capacity kW'],nrgvsecon['real gdp per␣
↪capita $'])
```

[29]:
```
SpearmanrResult(correlation=0.42678686304592384, pvalue=0.0016038790372016702)
```

A correlation of 0.43 isn't a strong correlation. What if we plotted these two against each other?

[30]:
```
x=nrgvsecon['installed capacity kW']
y=nrgvsecon['real gdp per capita $']

plt.xlabel('energy capacity')
plt.ylabel('real gdp')
plt.scatter(x,y);
```



From the scatterplot, would you say that a correlation exists?

From observations; * Fewer countries with high energy capacity * Countries with a higher GDP have little energy capacity

Hence no direct correlation between GDP and energy capacity

0.1.1 Taking population to account

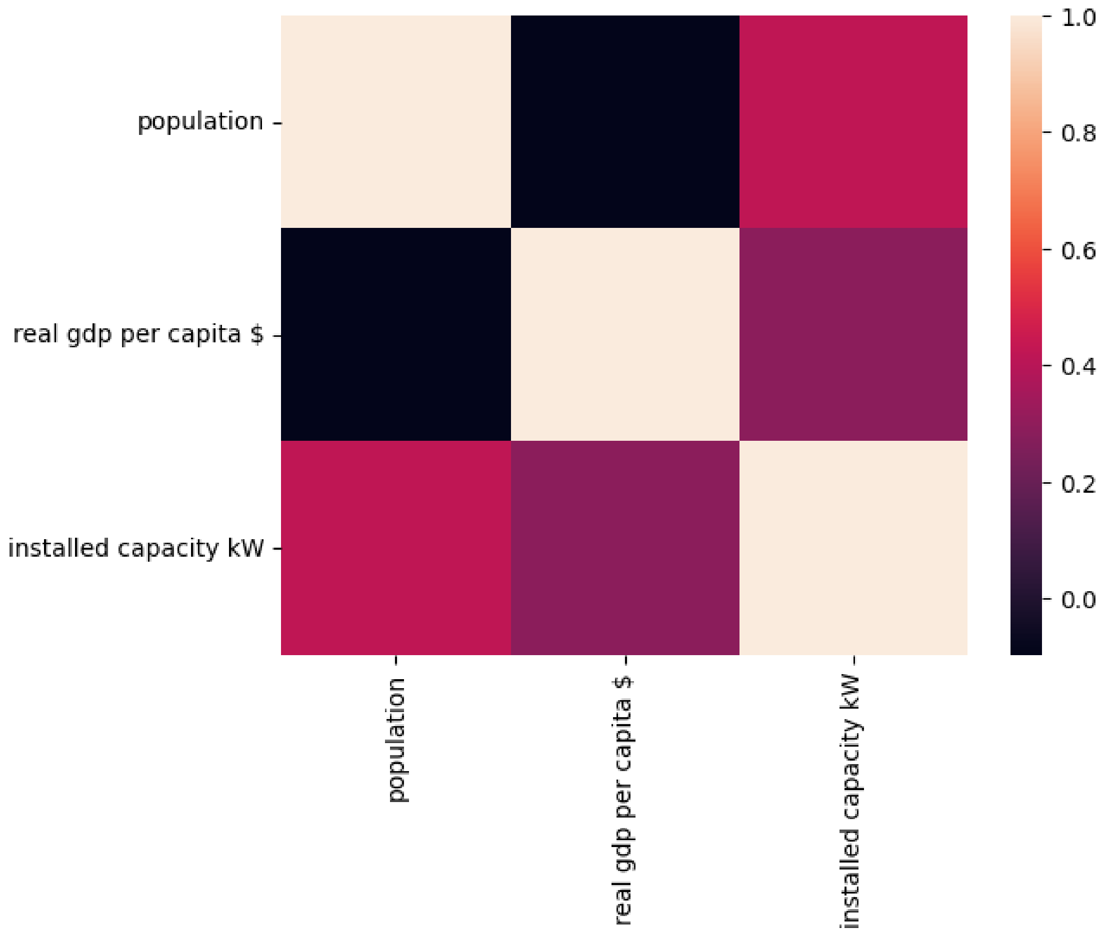
The plot above almost clearly indicates that there is no/a very small correlation between **total energy produced** and **gdp per capita**. This is due to several factors. Some countries, such as Seychelles, have extremely high gdp per capita, due to their low population. The total energy capacity, however, doesn't take population into account. How can we do this, with the data we have, for every country?

[31]:
```
pop_energy_gdp = nrgvsecon[["population", "real gdp per capita $", "installed␣
↪capacity kW"]]
pop_energy_gdp_corr = pop_energy_gdp.corr()
pop_energy_gdp_corr
```

[31]:
```
                       population  real gdp per capita $  \
population               1.000000              -0.096715
real gdp per capita $   -0.096715               1.000000
```

```
installed capacity kW    0.417738             0.284878

                       installed capacity kW
population                          0.417738
real gdp per capita $               0.284878
installed capacity kW               1.000000
```

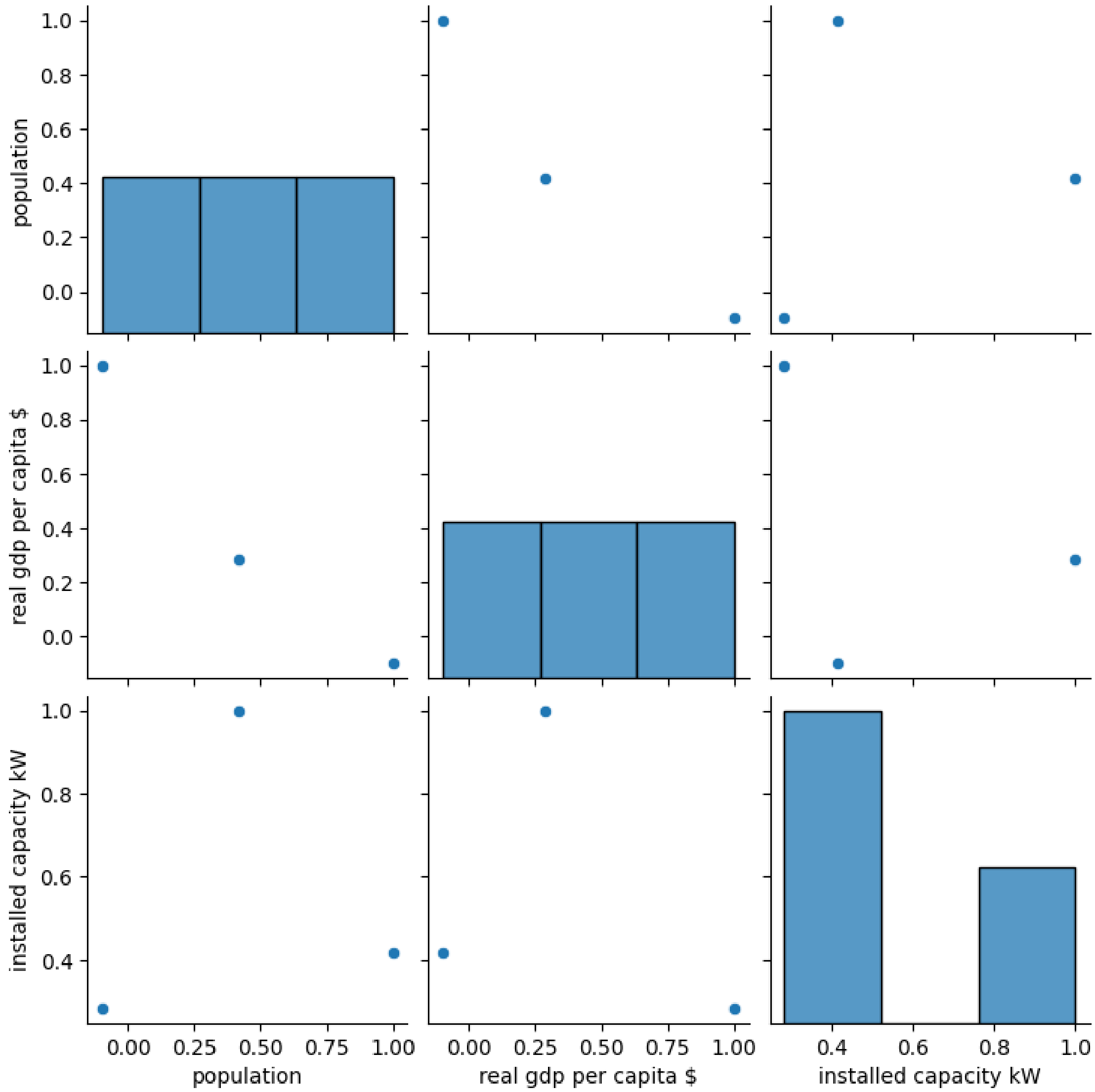
[32]:
```python
import seaborn as sns
sns.heatmap(pop_energy_gdp_corr);
```



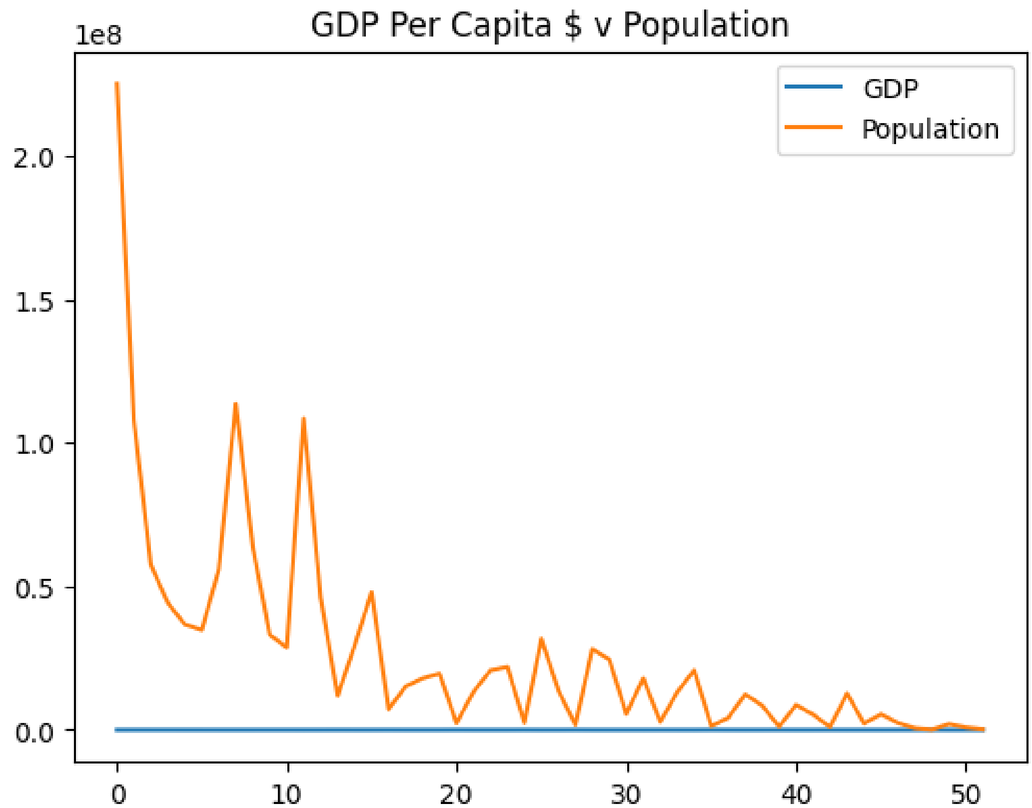
Can we find the correlation between the gdp per capita, and the variable that takes population into account?

Hint: how did we do this above?(Apart from the spearman's rank correlation, try search for other ways to find correlation, and see how these fair.e.g. Pearson correlation)

[33]:
```python
sns.pairplot(pop_energy_gdp_corr);
```



[34]:
```
plt.plot(nrgvsecon["real gdp per capita $"], label="GDP")
plt.plot(nrgvsecon["population"], label="Population")
plt.title("GDP Per Capita $ v Population")
plt.legend();
```

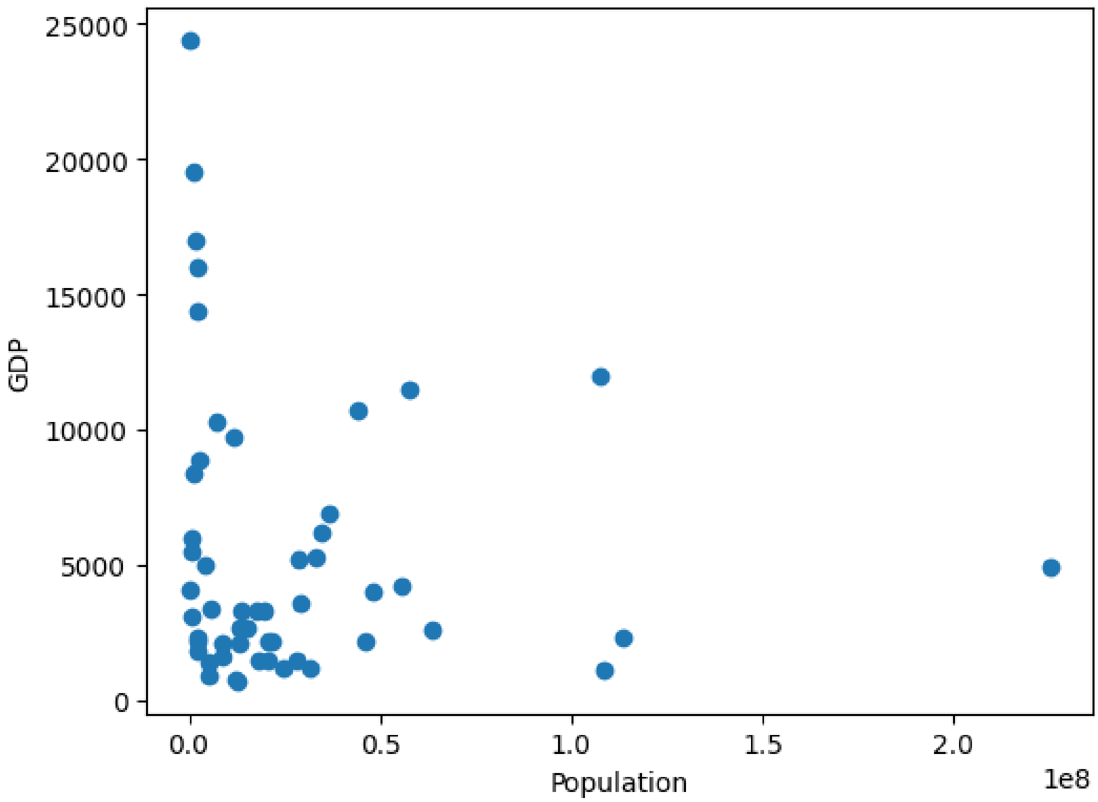


Can you plot the two variables against one another; gdp against the ‘other variable’

Hint: We mentioned this in class

Remember to label the axis

[35]:
```
x=nrgvsecon['population']
y=nrgvsecon['real gdp per capita $']

plt.xlabel('Population')
plt.ylabel('GDP')
plt.scatter(x,y);
```



Now, there are some outliers in our data, like South Africa, who produce a high amount of electricity, some of which goes to export, and Libya, who export a lot of fossil fuel despite their low population, causing high gdp per capita, among others.

Can we find a method to get rid of outliers like these?

Create new variables, that remove the outliers' data, and see whether the correlation is stronger, or weaker.

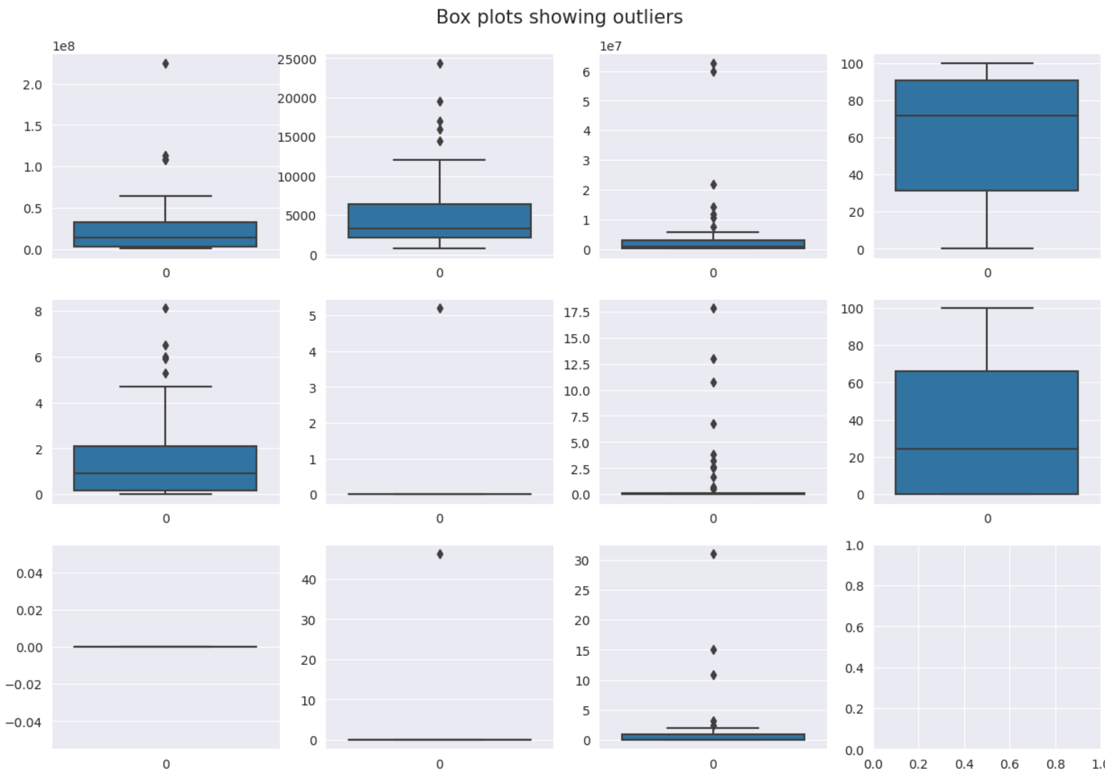
[36]:
```
nrgvsecon.head()
```

[36]:
```
        country   population  real gdp per capita $  installed capacity kW  \
0       nigeria  225082083.0                 4900.0             11691000.0
1         egypt  107770524.0                12000.0             59826000.0
2  south-africa   57516665.0                11500.0             62728000.0
3       algeria   44178884.0                10700.0             21694000.0
4       morocco   36738229.0                 6900.0             14187000.0

   fossil fuels  nuclear  solar  wind  hydroelectricity  tide and wave  \
0          78.1      0.0    0.2   0.0              21.7            0.0
1          88.7      0.0    1.0   2.5               7.7            0.0
2          87.9      5.2    1.6   2.6               2.5            0.0
3          98.9      0.0    0.9   0.0               0.1            0.0
```

```
4          81.6      0.0    1.1  13.0                4.4              0.0

   geothermal  biomass and waste
0         0.0                0.1
1         0.0                0.2
2         0.0                0.2
3         0.0                0.0
4         0.0                0.0
```

[ ]:
```python
# Use the Z-score method to identify outliers
z = np.abs(stats.zscore(data))
threshold = 3
outliers = np.where(z > threshold)

# Remove the outliers from the dataset
clean_data = data[~np.isin(range(len(data)), outliers)]
```

[37]:
```python
# Plotting boxplots for each of the numerical columns
sns.set_style('darkgrid')
fig, axes = plt.subplots(nrows = 3, ncols = 4, figsize = (15, 10))
fig.suptitle('Box plots showing outliers', y= 0.93, fontsize = 15)

for ax, data, name in zip(axes.flatten(), nrgvsecon, ['population','real gdp␣
 ↪per capita $',
                                                    'installed capacity␣
 ↪kW','fossil fuels', 'solar', 'nuclear',
                                                   'wind',␣
 ↪'hydroelectricity', 'tide and wave', 'geothermal',
                                                   'biomass and waste']):
    sns.boxplot(nrgvsecon[name], ax = ax)
```



- All have outliers except “hydroelectricity”, “tide and wave”, “fossil fuels”

[38]:
```
# We will use Quantile Flooring and Capping
print(nrgvsecon["population"].quantile(0.10))
print(nrgvsecon["population"].quantile(0.90))
```

```
1140407.1
57351464.0
```

[39]:
```
nrgvsecon["population"].describe()
```

[39]:
```
count    5.200000e+01
mean     2.681869e+07
std      3.913776e+07
min      9.701700e+04
25%      2.648908e+06
50%      1.349626e+07
75%      3.204675e+07
max      2.250821e+08
Name: population, dtype: float64
```

[40]:
```
nrgvsecon["population"] = np.where(nrgvsecon["population"]<1140407.1, 1140407.
↪1, nrgvsecon["population"])
```

```
nrgvsecon["population"] = np.where(nrgvsecon["population"]>57351464.0, 57351464.
↪0, nrgvsecon["population"])
# calculate the skewness
print(nrgvsecon["population"].skew())
```

```
0.8217679481122612
```

[41]:
```
# Dropping the outlier data points
index = nrgvsecon[(nrgvsecon['population'] >= 2.
↪250821e+08)|(nrgvsecon['population'] <= 9.701700e+04)].index
nrgvsecon.drop(index, inplace=True)
nrgvsecon['population'].describe()
```

[41]:
```
count    5.200000e+01
mean     2.048789e+07
std      1.935283e+07
min      1.140407e+06
25%      2.648908e+06
50%      1.349626e+07
75%      3.204675e+07
max      5.735146e+07
Name: population, dtype: float64
```

[42]:
```
print(nrgvsecon["real gdp per capita $"].quantile(0.10))
print(nrgvsecon["real gdp per capita $"].quantile(0.90))
```

```
1220.0
11950.0
```

[43]:
```
nrgvsecon["real gdp per capita $"].describe()
```

[43]:
```
count       52.000000
mean      5401.923077
std       5249.817565
min        700.000000
25%       2100.000000
50%       3300.000000
75%       6375.000000
max      24400.000000
Name: real gdp per capita $, dtype: float64
```

[44]:
```
nrgvsecon["real gdp per capita $"] = np.where(nrgvsecon["real gdp per capita␣
↪$"]<1220.0, 1220.0, nrgvsecon["real gdp per capita $"])
nrgvsecon["real gdp per capita $"] = np.where(nrgvsecon["real gdp per capita␣
↪$"]>11950.0, 11950.0, nrgvsecon["real gdp per capita $"])
# calculate the skewness
print(nrgvsecon["real gdp per capita $"].skew())
```

0.9565875862418413

[45]:
```
# Dropping the outlier data points
index = nrgvsecon[(nrgvsecon['real gdp per capita $'] >= 24400.
 ↪000000)|(nrgvsecon['real gdp per capita $'] <= 700.000000)].index
nrgvsecon.drop(index, inplace=True)
nrgvsecon['real gdp per capita $'].describe()
```

[45]:
```
count       52.000000
mean      4821.538462
std       3709.762629
min       1220.000000
25%       2100.000000
50%       3300.000000
75%       6375.000000
max      11950.000000
Name: real gdp per capita $, dtype: float64
```

[46]:
```
print(nrgvsecon["installed capacity kW"].quantile(0.10))
print(nrgvsecon["installed capacity kW"].quantile(0.90))
```

```
87400.0
10198799.999999996
```

[47]:
```
nrgvsecon["installed capacity kW"].describe()
```

[47]:
```
count    5.200000e+01
mean     4.680365e+06
std      1.214254e+07
min      2.800000e+04
25%      2.027500e+05
50%      7.110000e+05
75%      2.955500e+06
max      6.272800e+07
Name: installed capacity kW, dtype: float64
```

[48]:
```
nrgvsecon["installed capacity kW"] = np.where(nrgvsecon["installed capacity␣
 ↪kW"]<87400.0, 87400.0, nrgvsecon["installed capacity kW"])
nrgvsecon["installed capacity kW"] = np.where(nrgvsecon["installed capacity␣
 ↪kW"]>10198799.999999996, 10198799.999999996, nrgvsecon["installed capacity␣
 ↪kW"])
# calculate the skewness
print(nrgvsecon["installed capacity kW"].skew())
```

```
1.5974039425887363
```

[49]:
```
# Dropping the outlier data points
index = nrgvsecon[(nrgvsecon['installed capacity kW'] >= 6.
↪272800e+07)|(nrgvsecon['installed capacity kW'] <= 2.800000e+04)].index
nrgvsecon.drop(index, inplace=True)
nrgvsecon['installed capacity kW'].describe()
```

[49]:
```
count    5.200000e+01
mean     2.387773e+06
std      3.293286e+06
min      8.740000e+04
25%      2.027500e+05
50%      7.110000e+05
75%      2.955500e+06
max      1.019880e+07
Name: installed capacity kW, dtype: float64
```

[50]:
```
print(nrgvsecon["solar"].quantile(0.10))
print(nrgvsecon["solar"].quantile(0.90))
```

```
0.0
4.559999999999998
```

[51]:
```
nrgvsecon["solar"].describe()
```

[51]:
```
count    52.000000
mean      1.525000
std       1.946528
min       0.000000
25%       0.175000
50%       0.900000
75%       2.075000
max       8.100000
Name: solar, dtype: float64
```

[52]:
```
nrgvsecon["solar"] = np.where(nrgvsecon["solar"]<0.0, 0.0, nrgvsecon["solar"])
nrgvsecon["solar"] = np.where(nrgvsecon["solar"]>4.559999999999998, 4.
↪559999999999998, nrgvsecon["solar"])
# calculate the skewness
print(nrgvsecon["solar"].skew())
```

```
1.1136204685182292
```

[53]:
```
# Dropping the outlier data points
index = nrgvsecon[(nrgvsecon['solar'] >= 8.100000)|(nrgvsecon['solar'] <= 0.
↪000000)].index
nrgvsecon.drop(index, inplace=True)
nrgvsecon['solar'].describe()
```

```
[53]: count    45.000000
      mean      1.559111
      std       1.512782
      min       0.100000
      25%       0.200000
      50%       1.000000
      75%       2.400000
      max       4.560000
      Name: solar, dtype: float64
```

```
[54]: print(nrgvsecon["wind"].quantile(0.10))
      print(nrgvsecon["wind"].quantile(0.90))
```

```
0.0
3.3200000000000016
```

```
[55]: nrgvsecon["wind"].describe()
```

```
[55]: count    45.000000
      mean      1.404444
      std       3.680103
      min       0.000000
      25%       0.000000
      50%       0.000000
      75%       0.500000
      max      17.800000
      Name: wind, dtype: float64
```

```
[56]: nrgvsecon["wind"] = np.where(nrgvsecon["wind"]<0.0, 0.0, nrgvsecon["wind"])
      nrgvsecon["wind"] = np.where(nrgvsecon["wind"]>3.3200000000000016, 3.
       ↪3200000000000016, nrgvsecon["wind"])
      # calculate the skewness
      print(nrgvsecon["wind"].skew())
```

```
1.6438579263661781
```

```
[57]: index = nrgvsecon[(nrgvsecon['wind'] >= 17.800000)|(nrgvsecon['wind'] <= 0.
       ↪000000)].index
      nrgvsecon.drop(index, inplace=True)
      nrgvsecon['wind'].describe()
```

```
[57]: count    12.000000
      mean      2.308333
      std       1.160766
      min       0.500000
      25%       1.450000
      50%       2.600000
```

```
75%        3.320000
max        3.320000
Name: wind, dtype: float64
```

[58]:
```
print(nrgvsecon["biomass and waste"].quantile(0.10))
print(nrgvsecon["biomass and waste"].quantile(0.90))
```

```
0.0
2.2800000000000002
```

[59]:
```
nrgvsecon["biomass and waste"].describe()
```

[59]:
```
count    12.000000
mean      1.608333
std       4.278160
min       0.000000
25%       0.000000
50%       0.100000
75%       0.525000
max      15.000000
Name: biomass and waste, dtype: float64
```

[60]:
```
nrgvsecon["biomass and waste"] = np.where(nrgvsecon["biomass and waste"]<0.0, 0.
 ↪0, nrgvsecon["biomass and waste"])
nrgvsecon["biomass and waste"] = np.where(nrgvsecon["biomass and waste"]>2.
 ↪2800000000000002, 2.2800000000000002, nrgvsecon["biomass and waste"])
# calculate the skewness
print(nrgvsecon["biomass and waste"].skew())
```

```
1.5704563450423985
```

[61]:
```
index = nrgvsecon[(nrgvsecon['biomass and waste'] >=15.
 ↪000000)|(nrgvsecon['biomass and waste'] <= 0.000000)].index
nrgvsecon.drop(index, inplace=True)
nrgvsecon['biomass and waste'].describe()
```

[61]:
```
count    6.000000
mean     1.076667
std      1.005140
min      0.200000
25%      0.225000
50%      0.750000
75%      2.010000
max      2.280000
Name: biomass and waste, dtype: float64
```

[62]:
```
print(nrgvsecon["nuclear"].quantile(0.10))
print(nrgvsecon["nuclear"].quantile(0.90))
```

```
0.0
2.6
```

[63]:
```
nrgvsecon["nuclear"].describe()
```

[63]:
```
count    6.000000
mean     0.866667
std      2.122891
min      0.000000
25%      0.000000
50%      0.000000
75%      0.000000
max      5.200000
Name: nuclear, dtype: float64
```

[64]:
```
nrgvsecon["nuclear"] = np.where(nrgvsecon["nuclear"]<0.0, 0.0,␣
 ↪nrgvsecon["nuclear"])
nrgvsecon["nuclear"] = np.where(nrgvsecon["nuclear"]>2.6, 2.6,␣
 ↪nrgvsecon["nuclear"])
# calculate the skewness
print(nrgvsecon["nuclear"].skew())
```

```
2.449489742783178
```

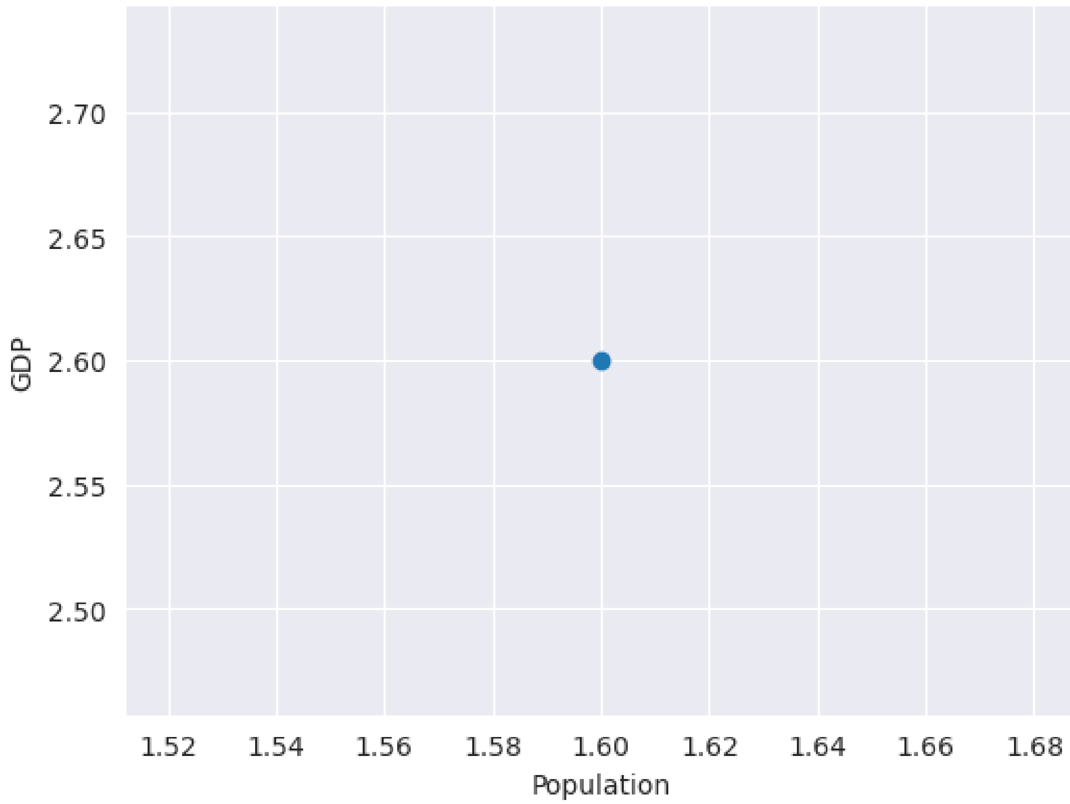
[65]:
```
index = nrgvsecon[(nrgvsecon['nuclear'] >=5.200000)|(nrgvsecon['nuclear'] <= 0.
 ↪000000)].index
nrgvsecon.drop(index, inplace=True)
nrgvsecon['nuclear'].describe()
```

[65]:
```
count    1.0
mean     2.6
std      NaN
min      2.6
25%      2.6
50%      2.6
75%      2.6
max      2.6
Name: nuclear, dtype: float64
```

print(nrgvsecon[“population”].quantile(0.10)) print(nrgvsecon[“population”].quantile(0.10)) print(nrgvsecon[“population”].quantile(0.10)) print(nrgvsecon[“population”].quantile(0.10))

Plot the new variables against one another. Remember to label the axis

[72]:
```
x=nrgvsecon['solar']
y=nrgvsecon['wind']

plt.xlabel('Population')
plt.ylabel('GDP')
plt.scatter(x,y);
```



[74]:
```
!jupyter nbconvert exploreafnrgvsec-exercise (Victor Ashioya).ipynb --to pdf
```

```
/bin/bash: -c: line 1: syntax error near unexpected token `('
/bin/bash: -c: line 1: `jupyter nbconvert exploreafnrgvsec-exercise (Victor
Ashioya).ipynb --to pdf'
```

This should more/less be similar to the plot we saw for income vs energy use per person!